Chapter - 5: Appendix

Import the Dataset and Necessary Libraries

In [ ]:
```
import pandas as pd
from tabulate import tabulate
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Specify the path to the Excel file
excel_file_path = "CDM_nfca.xlsx"

# Read the Excel file into a DataFrame
df = pd.DataFrame(pd.read_excel(excel_file_path))

# Display the first few rows of the dataframe
df.head(10)
```

index	Title	Theme	Subject
0	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Dodgems -- Or and Spooner
1	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Transport
2	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Transport
3	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Ark -- Lakin
4	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Dodgems

Primary Investigation

In [ ]:

```
# Display the shape of the dataset
print(df.shape)

# Display the information of the dataframe
df.info()
```

```
(76676, 44)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 76676 entries, 0 to 76675
Data columns (total 44 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Title                        76676 non-null  object
 1   Theme                        76387 non-null  object
 2   Subject                      76630 non-null  object
 3   Name                         61391 non-null  object
 4   Description                  76663 non-null  object
 5   Type                         76657 non-null  object
 6   Accession Number             76663 non-null  object
 7   Derivative                   17341 non-null  object
 8   Digital Master               76406 non-null  object
 9   Place Name                   64636 non-null  object
 10  Place Name (specific)        75991 non-null  object
 11  Geotag Location              56965 non-null  object
 12  Date of Subject              76019 non-null  object
 13  Period                       76507 non-null  object
 14  Creator                      75913 non-null  object
 15  Publisher                    76666 non-null  object
 16  Donor                        75181 non-null  object
 17  Collection Number            76435 non-null  object
 18  Collection Name              76537 non-null  object
 19  Digitiser                    76484 non-null  object
 20  Rights                       76666 non-null  object
 21  Permitted Uses               76666 non-null  object
 22  Contact for Further Uses     76666 non-null  object
 23  Date Created                 75803 non-null  object
 24  Date Digitised               76601 non-null  object
 25  Original Format (specific)   76554 non-null  object
 26  Original Format (general)    76666 non-null  object
 27  Physical Extent              52837 non-null  object
 28  Orientation                  76432 non-null  object
 29  Digital Format               76529 non-null  object
 30  Digital Extent               76007 non-null  object
 31  Digital Size                 76579 non-null  object
 32  Colour                       75828 non-null  object
 33  Sound                        7 non-null      object
 34  Quality                      344 non-null    object
 35  Identifier                   76582 non-null  object
 36  Language                     920 non-null    object
 37  OCLC number                  0 non-null      float64
 38  Date created                 76676 non-null  datetime64[ns]
 39  Date modified                76676 non-null  datetime64[ns]
 40  Reference URL                76676 non-null  object
 41  CONTENTdm number             76676 non-null  int64
 42  CONTENTdm file name          76676 non-null  object
 43  CONTENTdm file path          76676 non-null  object
dtypes: datetime64[ns](2), float64(1), int64(1), object(40)
memory usage: 25.7+ MB
```

In [ ]:

```
## MISSING VALUES

# Count the number of missing values in each column
```

```
missing_counts = df.isna().sum()
missing_percentile = (df.isna().sum()/76676) * 100

# Display the missing value counts
missing_data = pd.DataFrame({
    'Missing Count': missing_counts,
    'Missing Percentage': missing_percentile
})
missing_data
```

index	Missing Count	Missing Percentage
Title	0	0
Theme	289	0.37691063696593463
Subject	46	0.05999269654129063
Name	15285	19.93452970942668
Description	13	0.01695445771819083
Type	19	0.024779592049663516
Accession Number	13	0.01695445771819083
Derivative	59335	77.38405759298868
Digital Master	270	0.35213104491627106
Place Name	12040	15.702436225155198

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Data Pre-processing

In [ ]:

```
## Treating Missing Values
# Remove missing values in columns which have less than 5% of missing values
# Filter out the columns where the missing percentage is less than 5%
columns_to_treat = missing_data[missing_percentile < 5].index
df = df.dropna(subset=columns_to_treat)

# Display the treated  missing value counts and percentages
missing_counts = df.isna().sum()
missing_percentile = df.isna().sum()/76676 * 100
missing_data = pd.DataFrame({
    'Missing Count': missing_counts,
    'Missing Percentage': missing_percentile
})
missing_data
```

index	Missing Count	Missing Percentage
Title	0	0
Theme	0	0
Subject	0	0
Name	14462	18.861182116959675
Description	0	0
Type	0	0
Accession Number	0	0
Derivative	56263	73.37758881527466
Digital Master	0	0
Place Name	11163	14.558662423704941

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In [ ]:

```
# Get the list of distinct themes
distinct_themes = df['Theme'].unique()

# Print the distinct themes after
print("Distinct Themes")
for theme in distinct_themes:
    print(theme)

print("Number of Unique Themes: "+ str(len(distinct_themes)))
```

Distinct Themes
Fairs
Amusement parks
Circus
Steam-engines -- Exhibitions
Fetes
Fairs
Great Ouse River (England)
Church buildings
Exhibitions
Machinery models
Factories
Museums
Zoos
Fairgrounds
Seaside Entertainment
Factories; Fairs
Amusement Parks
Museums; Steam-engines -- Exhibitions
Cemeteries
Road rollers
Weddings
Parks
Seaside resorts
Rivers
Traction-engines
Buses
Fairs; Exhibitions
Fairs; Exhibitions; Variety and Music Hall
Motion picture theaters
Variety and Music Hall; Exhibitions
Steam-engines -- Exhibitions; Fairs; Exhibitions
Bingo
Ploughing
Taverns (Inns)
Plowing
Castles
Narrow gauge railroads
Cafeterias
Amusement parks; Zoos
Aquariums
Circus; Amusement parks
Circus; Exhibitions
Circus; Zoos
Zoos; Circus
Music-halls
Circus; Seaside Entertainment
Speedway motorcycle racing
Exhibition
fairs
Fairs; Circus
Exhibitions; Variety and Music Hall
Circus; Fair
Fairs; Amusement parks
Amusement parks
Number of Unique Themes: 54

In [ ]:
```
## Mapping Redundant and Inconsistent values in ‘Theme’
themes_mapping = {
    'Fetes' : 'Fairs',
    'Fairs ' : 'Fairs',
    'Fairs; Traction-engines; Steam-engines -- Exhibitions; Steam-engines;':
    'Fairs; Steam-engines -- Exhibitions': 'Fairs',
    'Fairs; Amusement Parks and Theme Parks; Fixed Entertainment Venue':'Fai
    'Fairs; Amusement parks': 'Fairs',
    'fairs':'Fairs',
    'Fairs; Circus':'Fairs',
    'Fairs; Circus; Exhibitions':'Fairs',
    'Fairs; Exhibitions':'Fairs',
    'Fairs; Exhibitions; Variety and Music Hall':'Fairs',
    'Circus; Amusement parks': 'Circus',
    'Circus; Exhibitions': 'Circus',
    'Circus; Zoos' : 'Circus',
    'Zoos; Circus' : 'Circus',
    'Fixed Entertainment Venue; Circus;':'Circus',
    'Circus; Seaside Entertainment': 'Circus',
    'Circus; Fair':'Circus',
    'Circus; Music Hall and Variety':'Circus',
    'Circus;':'Circus',
    'Circus; Variety and Music Hall;' : 'Circus',
    'Circus; Fairs;': 'Circus',
    'Circus; Zoos;': 'Circus',
    'Circus; Variety and Music Hall':'Circus',
    'Seaside Resorts (Seaside Entertainment); Performers': 'Seaside Resorts
    'Seaside Resorts (Seaside Entertainment): Performers': 'Seaside Resorts
    'Seaside Resorts (Seaside Entertainment): Amusement Parks':'Seaside Reso
    'Great Ouse River (England)':'Seaside Resorts (Seaside Entertainment)',
    'Seaside Entertainment':'Seaside Resorts (Seaside Entertainment)',
    'Rivers' :'Seaside Resorts (Seaside Entertainment)',
    'Seaside Resorts (Seaside Entertainment)':'Seaside Resorts (Seaside Ente
    'Seaside resorts':'Seaside Resorts (Seaside Entertainment)',
    'Variety and Music Hall; Circus;':'Variety and Music Hall',
    'Variety and Music Hall; Circus; Exhibitions' : 'Variety and Music Hall'
    'Amusement Parks and Theme Parks;': 'Amusement Parks',
    'Amusement Parks and Theme Parks; Seaside Entertainment' : 'Amusement Pa
    'Amusement parks; Zoos': 'Amusement Parks',
    'Amusement parks; Zoos ': 'Amusement Parks',
    'Amusement parks ':'Amusement Parks',
    'Amusement parks':'Amusement Parks',
    'Amusement Parks and Theme Parks; Circus':'Amusement Parks',
    'Exhibitions; Variety and Music Hall' : 'Exhibition',
    'Exhibitions; Circus; Variety and Music Hall' : 'Exhibition',
    'Exhibition; Variety and Music Hall' : 'Exhibition',
    'Exhibitions; Circus':'Exhibition',
    'Exhibition; Variety and Music Hall; Circus':'Exhibition',
    'Exhibitions; Fairs':'Exhibition',
    'Performers; Circus':'Performers',
    'Showpeople':'Performers',
    'Performer':'Performers',
    'Performers; Seaside Entertainment':'Performers',
    'Peterborough Cathedral':'Church buildings',
    'Cemeteries':'Church buildings',
```

```
    'Fairground':'Exhibitions',
    'Music Hall and Variety':'Exhibitions',
    'Fairgrounds; Exhibitions':'Exhibitions',
    'Fixed Enertainment Venue':'Exhibitions',
    'Traction-engines; Steam-engines -- Exhibitions; Steam-engines;':'Exhibi
    'Fixed Entertainment Venue;':'Exhibitions',
    'Variety and Music Hall;':'Exhibitions',
    'Steam-engines -- Exhibitions; Circus':'Exhibitions',
    'Speedway motorcycle racing':'Exhibitions',
    'Exhibition':'Exhibitions',
    'Steam-engines -- Exhibitions ':'Exhibitions',
    'NFA Logo opacity 30':'Exhibitions',
    'Exhibition; Circus':'Exhibitions',
    'Machinery models':'Exhibitions',
    'Steam-engines':'Exhibitions',
    'Museums; Steam-engines -- Exhibitions':'Exhibitions',
    'Variety and Music Hall; Exhibitions':'Exhibitions',
    'Steam-engines -- Exhibitions; Fairs; Exhibitions':'Exhibitions',
    'Variety and Music Hall':'Exhibitions',
    'Traction-engines':'Exhibitions',
    'Buses':'Exhibitions',
    'Motion picture theaters':'Exhibitions',
    'Steam-engines -- Exhibitions':'Exhibitions',
    'Narrow gauge railroads':'Exhibitions',
    'Plowing':'Ploughing',
    'Factories; Fairs':'Factories',
    'Fairgrounds':'Fairs'
}

# Apply the mapping to the 'Theme' column
df['Theme'] = df['Theme'].replace(themes_mapping)

# Get the updated list of distinct themes after grouping
distinct_themes = df['Theme'].unique()

print("Number of Unique Themes: "+ str(len(distinct_themes)))
```

```
Number of Unique Themes: 20
```

In [ ]:

```
# Extract individual years from the 'Period' column to create a new 'Year' c
df['Year'] = df['Period'].str.extract(r'(\d{4})')
```

In [ ]:

```
# install NLTK package
!pip install nltk
```

```
Collecting nltk
  Downloading nltk-3.8.1-py3-none-any.whl (1.5 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.5/1.5 MB 45.9 MB/s eta 0:00:
00
Requirement already satisfied: regex>=2021.8.3 in /opt/conda/lib/python3.9/s
ite-packages (from nltk) (2023.5.5)
Requirement already satisfied: joblib in /opt/conda/lib/python3.9/site-packa
ges (from nltk) (1.2.0)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.9/site-package
s (from nltk) (4.65.0)
Requirement already satisfied: click in /opt/conda/lib/python3.9/site-packag
es (from nltk) (8.1.3)
Installing collected packages: nltk
Successfully installed nltk-3.8.1
```

In [ ]:

```
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import string

# Download NLTK resources
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('maxent_ne_chunker')
nltk.download('words')
nltk.download('averaged_perceptron_tagger')

# Load the set of English stopwords
stop_words = set(stopwords.words('english'))

# Function to remove named entities from text
def remove_named_entities(text):
    tokens = word_tokenize(text)
    tagged_tokens = nltk.pos_tag(tokens)
    non_entities = [word for word, tag in tagged_tokens if not is_named_enti
    return ' '.join(non_entities)

# Function to check if a POS tag represents a named entity
def is_named_entity(tag):
    return tag in ['NNP', 'NNPS']

# Function to tokenize a text and remove stop words, dates, punctuation mark
def tokenize_text(text):
    words = word_tokenize(text)
    words = [word.lower() for word in words]
    words = [word for word in words if word not in string.punctuation]
    words = [word for word in words if word not in stop_words]
    words = [word for word in words if not
             any(char.isdigit() for char in word) and
              word != '-' and word != "'s" and
              word != "photographed" and
              word != "photograph" and
              word != "photograph " and
              word != "digitisation" and
```

```
            word != "number" and
            word != "registration" and
            word != '--'  and
            word != '_' ]
    lemmatizer = WordNetLemmatizer()
    words = [lemmatizer.lemmatize(word) for word in words]
    return words

# Combine 'Description', 'Subject' and 'Theme' columns
df['tags'] = df['Description'].fillna('') + ' ' + df['Subject'].fillna('') +

# Remove named entities from 'tags' column
df['tags'] = df['tags'].apply(remove_named_entities)

# Tokenize the cleaned text
df['tags'] = df['tags'].apply(tokenize_text)

# Display the DataFrame with the 'tags' column containing the cleaned and to
df.head()
```

```
[nltk_data] Downloading package punkt to /home/noteable/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/noteable/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /home/noteable/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package maxent_ne_chunker to
[nltk_data]     /home/noteable/nltk_data...
[nltk_data]   Package maxent_ne_chunker is already up-to-date!
[nltk_data] Downloading package words to /home/noteable/nltk_data...
[nltk_data]   Package words is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /home/noteable/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```

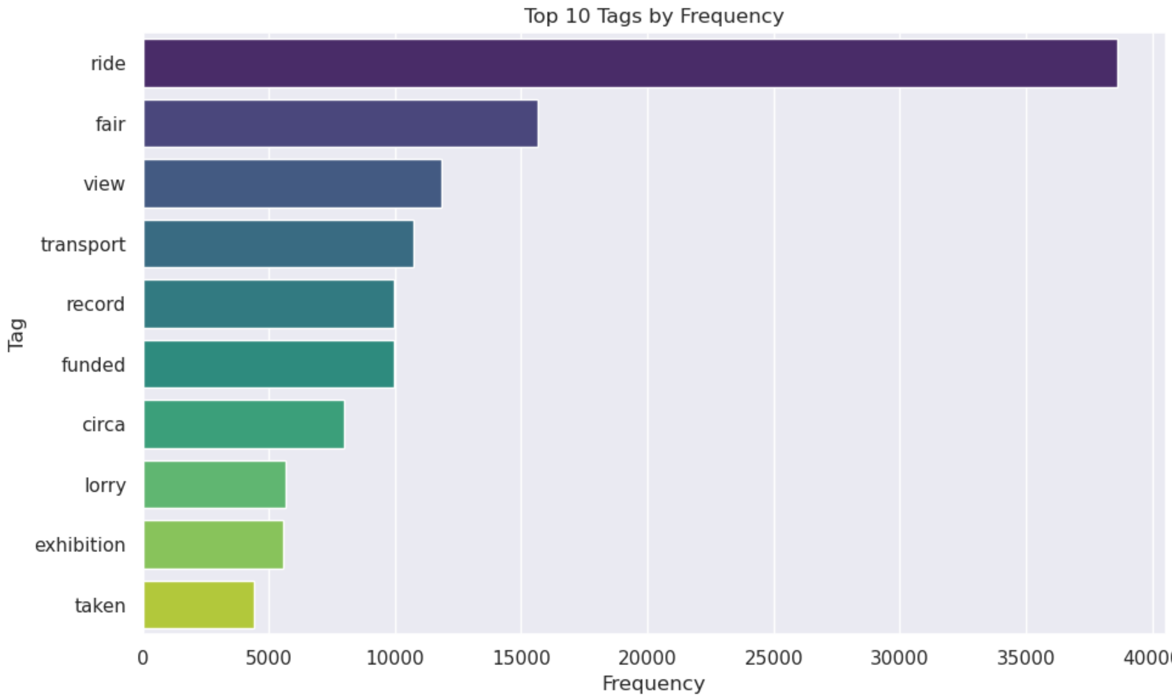
index	Title	Theme	Subject
0	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Dodgems -- Or and Spooner
1	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Transport
2	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Transport
3	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Ark -- Lakin
4	Jack Leeson photograph, Nottingham Goose Fair, 1958.	Fairs	Amusement rides -- Dodgems

Exploratory Data Analysis(EDA)

In [ ]:

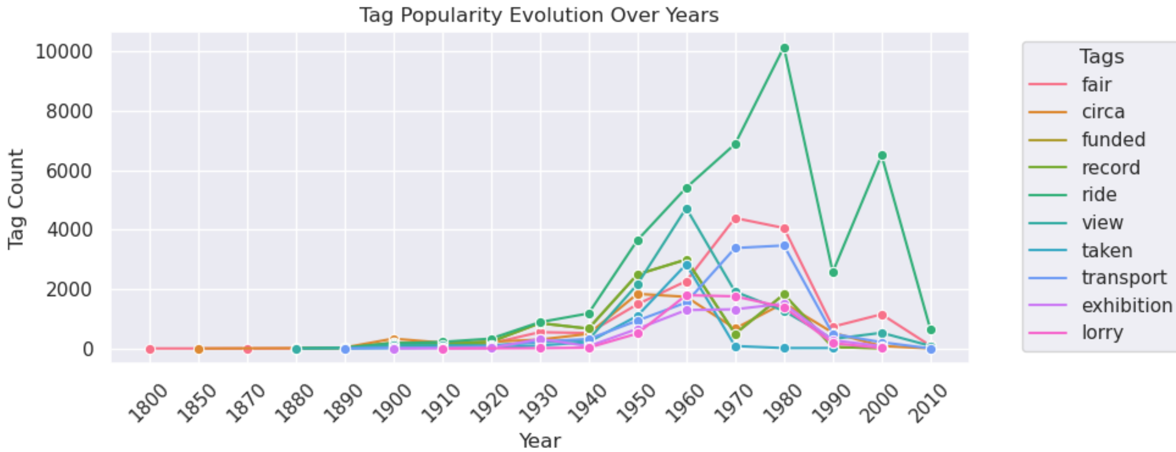
```
# Top 10 Tags by Frequency
import seaborn as sns
import matplotlib.pyplot as plt
from collections import Counter

tags_data = df['tags'].tolist()

# Flatten the list of tokens into a single list
all_tags = [tag for tags in tags_data for tag in tags]

# Compute the frequency of each tag
tag_frequencies = Counter(all_tags)

# Convert the tag frequencies to a DataFrame for better visualization
tag_frequency_df = pd.DataFrame(tag_frequencies.items(), columns=['Tag', 'Fr

# Sort the DataFrame in descending order based on tag frequency
tag_frequency_df = tag_frequency_df.sort_values(by='Frequency', ascending=Fa

# Set up the plot using seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x='Frequency', y='Tag', data=tag_frequency_df.head(10), palette=
sns.set(rc={"figure.figsize":(2, 4)})
# Customise the plot
```

```
plt.xlabel('Frequency')
plt.ylabel('Tag')
plt.title('Top 10 Tags by Frequency')
plt.tight_layout()

# Show the plot
plt.show()
```



In [ ]:

```
# Tag Popularity Evolution Over Years
# Select a subset of tags for visualisation (e.g., top 10 most common tags)
top_tags = tag_count_by_year.groupby('tags')['tag_count'].sum().nlargest(10)
top_tags_data = tag_count_by_year[tag_count_by_year['tags'].isin(top_tags)]

sns.lineplot(x='Year', y='tag_count', hue='tags', data=top_tags_data, marker
sns.set(rc={"figure.figsize":(10, 5)}) #width=3, #height=4
plt.xlabel('Year')
plt.ylabel('Tag Count')
plt.title('Tag Popularity Evolution Over Years')
plt.xticks(rotation=45)
plt.legend(title='Tags', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



In [ ]:
```
!pip install wordcloud
```

```
Collecting wordcloud
  Downloading wordcloud-1.9.2-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_
x86_64.whl (460 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 460.4/460.4 kB 17.8 MB/s eta 0:0
0:00
Requirement already satisfied: pillow in /opt/conda/lib/python3.9/site-packa
ges (from wordcloud) (9.2.0)
Requirement already satisfied: numpy>=1.6.1 in /opt/conda/lib/python3.9/site
-packages (from wordcloud) (1.23.5)
Requirement already satisfied: matplotlib in /opt/conda/lib/python3.9/site-p
ackages (from wordcloud) (3.6.0)
Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python
3.9/site-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in /opt/conda/lib/python3.9/
site-packages (from matplotlib->wordcloud) (3.0.9)
Requirement already satisfied: contourpy>=1.0.1 in /opt/conda/lib/python3.9/
site-packages (from matplotlib->wordcloud) (1.0.5)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.9/site
-packages (from matplotlib->wordcloud) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /opt/conda/lib/python3.
9/site-packages (from matplotlib->wordcloud) (4.37.4)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/python3.
9/site-packages (from matplotlib->wordcloud) (1.4.4)
Requirement already satisfied: packaging>=20.0 in /opt/conda/lib/python3.9/s
ite-packages (from matplotlib->wordcloud) (23.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.9/site-pac
kages (from python-dateutil>=2.7->matplotlib->wordcloud) (1.16.0)
Installing collected packages: wordcloud
Successfully installed wordcloud-1.9.2
```

In [ ]:
```
from wordcloud import WordCloud

# Group by 'Theme' and count the frequency of each theme
theme_counts = df['Theme'].value_counts()

# Create a WordCloud object
wordcloud = WordCloud(width=800, height=400, background_color='white').gener

# Display the word cloud using matplotlib
```

```
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Popular Themes')
plt.show()
```

In [ ]:
```
# Calculate the frequency of each theme
theme_freq = df['Theme'].value_counts()

# Create a new DataFrame to store the frequency table
theme_freq_table = pd.DataFrame({'Theme': theme_freq.index, 'Frequency': the

# Display the frequency table
theme_freq_table
```

index	Theme	Frequency
0	Fairs	54749
1	Amusement Parks	8237
2	Exhibitions	6342
3	Circus	2650
4	Factories	1016
5	Museums	247
6	Zoos	118
7	Seaside Resorts (Seaside Entertainment)	44
8	Road rollers	34
9	Church buildings	26

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Implementing Tag Recommendation Systems

In [ ]:
```
# Install the Gensim package to import Word2Vec and LDA model
!pip install gensim
```

```
Collecting gensim
  Downloading gensim-4.3.2-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86
_64.whl (26.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 26.6/26.6 MB 54.9 MB/s eta 0:0
0:00
Collecting smart-open>=1.8.1
  Downloading smart_open-6.3.0-py3-none-any.whl (56 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 56.8/56.8 kB 12.9 MB/s eta 0:0
0:00
Requirement already satisfied: numpy>=1.18.5 in /opt/conda/lib/python3.9/sit
e-packages (from gensim) (1.23.5)
Requirement already satisfied: scipy>=1.7.0 in /opt/conda/lib/python3.9/site
-packages (from gensim) (1.9.1)
Installing collected packages: smart-open, gensim
Successfully installed gensim-4.3.2 smart-open-6.3.0
```

Word2Vec

In [ ]:
```
import pandas as pd
import numpy as np
from gensim.models import Word2Vec
from sklearn.metrics.pairwise import cosine_similarity
import random
import time

# Set a random seed for reproducibility
random.seed(42)

def tag_recommendation(df, given_tag, top_N=5):
    tag_list = df['tags'].tolist()

    # Train a Word2Vec model
    model = Word2Vec(sentences=tag_list, vector_size=100, window=5, min_coun

    # Dictionary to store mappings
    tag_embedding_map = {}
    embedding_dim = 100
    # Function to get tag embedding
    def get_tag_embedding(tag, model, embedding_dim):
        if tag in model.wv:
            embedding = model.wv[tag]
            #print(f"Word Embedding of '{tag}': {embedding}")
            return embedding
        elif tag in tag_embedding_map:
            return tag_embedding_map[tag]
        else:
            # Generate a random embedding for the out-of-vocabulary tag
            random_embedding = np.random.rand(embedding_dim)
            tag_embedding_map[tag] = random_embedding
            return random_embedding
```

```
    # Get the word embedding for the given tag
    given_tag_embedding = get_tag_embedding(given_tag, model, embedding_dim)

    if given_tag_embedding is not None:
        # Measure the start time
        start_time = time.time()

        # Calculate the cosine similarity between the word embeddings of the
        similarity_scores = []
        unique_tokens = set(token for tokens_list in tag_list for token in t
        for tag in unique_tokens:
            tag_embedding = get_tag_embedding(tag, model, embedding_dim)
            if tag_embedding is not None:
                similarity_score = cosine_similarity([given_tag_embedding],
                if similarity_score >= 0.5:
                    similarity_scores.append((tag, similarity_score))

        # Sort the tags based on similarity scores in descending order
        similarity_scores.sort(key=lambda x: x[1], reverse=True)

        # Get the top-N recommended tags
        recommended_tags = similarity_scores[:top_N]

        # Measure the end time
        end_time = time.time()

        # Calculate the recommendation response time
        response_time = end_time - start_time

        # Get the top-N recommended tags
        total_recommended_tags = [tag for tag, _ in similarity_scores]

        # Display the total number of recommendations found
        total_recommendations = len(total_recommended_tags)
        print(f"Total Recommendations found: {total_recommendations}")

        # Display the recommendation response time
        print(f"Recommendation Response Time: {response_time:.4f} seconds")

        return  recommended_tags, total_recommended_tags ## JUST change to t
    else:
        return None

# User-defined given tag
given_tag = input("Enter your search variable : ")
recommended_tags_word2vec, total_recommendations_word2vec = tag_recommendati

# JUST comment these for overlap and Shannon’s Entropy
if recommended_tags_word2vec is not None:
    print("Recommended Tags and their Cosine Similarities:")
    for tag, similarity in recommended_tags_word2vec:
        print(f"Tag: {tag}, Cosine Similarity: {similarity:.4f}")
else:
    print("Given tag not found in the Word2Vec model.")
```

```
Total Recommendations found: 3251
Recommendation Response Time: 1.1193 seconds
Recommended Tags and their Cosine Similarities:
Tag: waltzer, Cosine Similarity: 1.0000
Tag: fogged, Cosine Similarity: 0.9758
Tag: rafter, Cosine Similarity: 0.9730
Tag: cyclone, Cosine Similarity: 0.9717
Tag: chair, Cosine Similarity: 0.9716
```

LDA

In [ ]:

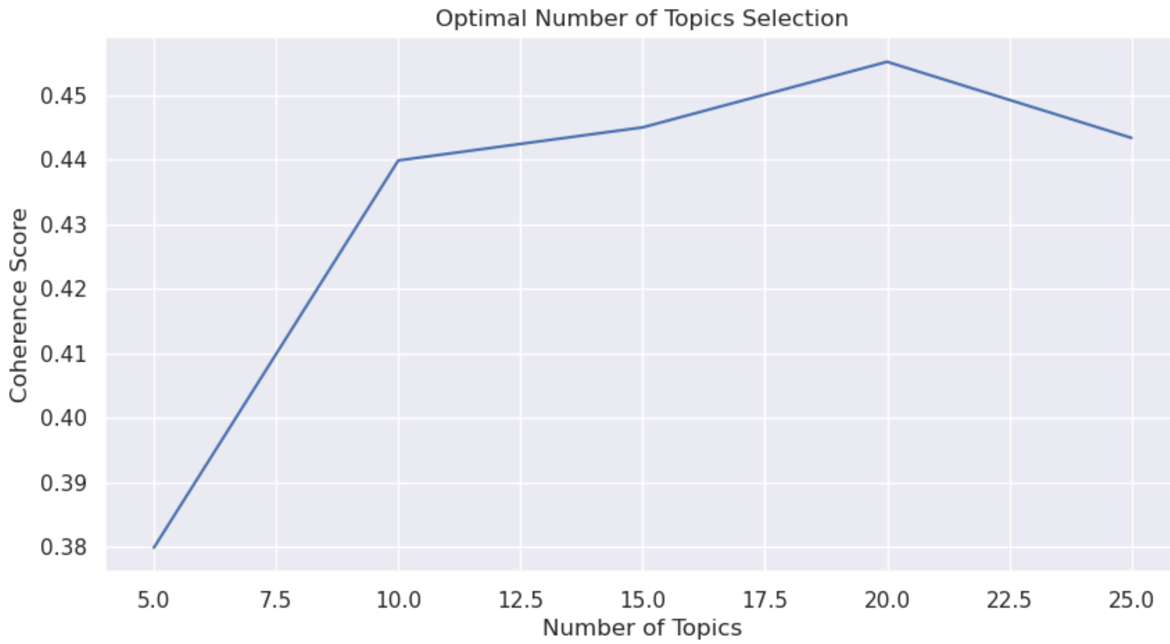
```
from gensim.models import CoherenceModel
from gensim.corpora import Dictionary
from gensim.models import LdaModel
import matplotlib.pyplot as plt

# Convert ‘tags’ column to a list
tags = df['tags'].tolist()

# Create a dictionary and corpus for the LDA model
dictionary = Dictionary(tags)
corpus = [dictionary.doc2bow(doc) for doc in tags]

# Calculate coherence scores for different topic numbers
coherence_scores = []
for num_topics in range(5, 30, 5):
    lda_model = LdaModel(corpus, num_topics=num_topics, id2word=dictionary,
    coherence_model = CoherenceModel(model=lda_model, texts=tags, dictionary
    coherence_scores.append(coherence_model.get_coherence())

# Plot coherence scores
plt.plot(range(5, 30, 5), coherence_scores)
plt.xlabel("Number of Topics")
plt.ylabel("Coherence Score")
plt.title("Optimal Number of Topics Selection")
plt.show()
```



In [ ]:
```
# Install pyLDAviz package
!pip install pyLDAvis
```

```
Collecting pyLDAvis
  Downloading pyLDAvis-3.4.1-py3-none-any.whl (2.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.6/2.6 MB 55.9 MB/s eta 0:00:
00
Requirement already satisfied: jinja2 in /opt/conda/lib/python3.9/site-packa
ges (from pyLDAvis) (3.1.2)
Requirement already satisfied: joblib>=1.2.0 in /opt/conda/lib/python3.9/sit
e-packages (from pyLDAvis) (1.2.0)
Collecting numpy>=1.24.2
  Downloading numpy-1.25.2-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86
_64.whl (18.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 57.0 MB/s eta 0:0
0:00
Collecting pandas>=2.0.0
  Downloading pandas-2.0.3-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86
_64.whl (12.4 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12.4/12.4 MB 76.3 MB/s eta 0:0
0:00
Requirement already satisfied: scipy in /opt/conda/lib/python3.9/site-packag
es (from pyLDAvis) (1.9.1)
Requirement already satisfied: gensim in /opt/conda/lib/python3.9/site-packa
ges (from pyLDAvis) (4.3.2)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.9/site-p
ackages (from pyLDAvis) (68.1.0)
Collecting funcy
  Downloading funcy-2.0-py2.py3-none-any.whl (30 kB)
Requirement already satisfied: numexpr in /opt/conda/lib/python3.9/site-pack
ages (from pyLDAvis) (2.8.3)
Requirement already satisfied: scikit-learn>=1.0.0 in /opt/conda/lib/python
3.9/site-packages (from pyLDAvis) (1.1.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/lib/pyth
on3.9/site-packages (from pandas>=2.0.0->pyLDAvis) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.9/site
-packages (from pandas>=2.0.0->pyLDAvis) (2023.3)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.9/si
te-packages (from pandas>=2.0.0->pyLDAvis) (2022.4)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/conda/lib/python
3.9/site-packages (from scikit-learn>=1.0.0->pyLDAvis) (3.1.0)
Collecting numpy>=1.24.2
  Downloading numpy-1.24.4-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86
_64.whl (17.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 17.3/17.3 MB 68.0 MB/s eta 0:0
0:00
Requirement already satisfied: smart-open>=1.8.1 in /opt/conda/lib/python3.
9/site-packages (from gensim->pyLDAvis) (6.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/conda/lib/python3.9/s
ite-packages (from jinja2->pyLDAvis) (2.1.2)
Requirement already satisfied: packaging in /opt/conda/lib/python3.9/site-pa
ckages (from numexpr->pyLDAvis) (23.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.9/site-pac
kages (from python-dateutil>=2.8.2->pandas>=2.0.0->pyLDAvis) (1.16.0)
Installing collected packages: funcy, numpy, pandas, pyLDAvis
  Attempting uninstall: numpy
    Found existing installation: numpy 1.23.5
    Uninstalling numpy-1.23.5:
      Successfully uninstalled numpy-1.23.5
```

```
  Attempting uninstall: pandas
    Found existing installation: pandas 1.5.3
    Uninstalling pandas-1.5.3:
      Successfully uninstalled pandas-1.5.3
ERROR: pip's dependency resolver does not currently take into account all th
e packages that are installed. This behaviour is the source of the following
dependency conflicts.
numba 0.56.2 requires numpy<1.24,>=1.18, but you have numpy 1.24.4 which is
incompatible.
noteable 2.0.0 requires pandas<2.0.0,>=1.5.3, but you have pandas 2.0.3 whic
h is incompatible.
fugue 0.8.3 requires pandas<2,>=1.2.0, but you have pandas 2.0.3 which is in
compatible.
flytekit 1.2.11 requires numpy<1.24.0, but you have numpy 1.24.4 which is in
compatible.
flytekit 1.2.11 requires pandas<2.0.0,>=1.0.0, but you have pandas 2.0.3 whi
ch is incompatible.
flytekit 1.2.11 requires protobuf<4,>=3.6.1, but you have protobuf 4.21.7 wh
ich is incompatible.
dx 1.3.0 requires pandas<2.0.0,>=1.3.5, but you have pandas 2.0.3 which is i
ncompatible.
databricks-sql-connector 2.5.2 requires pandas<2.0.0,>=1.2.5, but you have p
andas 2.0.3 which is incompatible.
Successfully installed funcy-2.0 numpy-1.24.4 pandas-2.0.3 pyLDAvis-3.4.1
```

In [ ]:

```python
import pyLDAvis
import pyLDAvis.gensim
# Train an LDA model
lda_model = LdaModel(corpus, num_topics=20, id2word=dictionary, passes=10)

# Prepare the visualisation
vis = pyLDAvis.gensim.prepare(lda_model, corpus, dictionary)

# Visualise the topics
pyLDAvis.enable_notebook()
pyLDAvis.display(vis)
```

Out[ ]:

In [ ]:

```python
#Implement Tag Recommendation System
import pandas as pd
from gensim.corpora import Dictionary
from gensim.models import LdaModel
from gensim.models import TfidfModel
from sklearn.metrics.pairwise import cosine_similarity
import time

def lda_tag_recommendation(df, given_tag, top_N=5):
    tags= df['tags'].tolist()

    # Create a dictionary and corpus for the LDA model
    dictionary = Dictionary(tags)
    corpus = [dictionary.doc2bow(doc) for doc in tags]

    # Train a TF-IDF model on the corpus
    tfidf = TfidfModel(corpus)
```

```
corpus_tfidf = tfidf[corpus]

# Train an LDA model
num_topics = 20
lda_model = LdaModel(corpus_tfidf, num_topics=num_topics, id2word=dictio

# Function to get topic distribution for a given document
def get_document_topics(tags):
    bow = dictionary.doc2bow(tags)
    tfidf_weights = tfidf[bow]
    topics = lda_model.get_document_topics(tfidf_weights)
    return topics

# Get topic distribution for the given tag
given_tag_topics = get_document_topics(given_tag.split())

# Get the most relevant tags for the given tag based on topic distributi
recommended_tags = []
total_recommended_tags = set()  # Use a set to avoid duplicate tags
for topic, score in sorted(given_tag_topics, key=lambda x: x[1], reverse
    topic_tags = lda_model.show_topic(topic, topn=5)  # Get the top 5 wo
    recommended_tags.extend([tag for tag, _ in topic_tags])
    total_recommended_tags.update([tag for tag, _ in topic_tags])

num_recommended_tags = len(total_recommended_tags)  # Count the number o


# Calculate recommendation response time
start_time = time.time()

# Calculate the cosine similarity between the topic distribution of the
similarity_scores = []
for tag in recommended_tags:
    tag_topics = get_document_topics(tag.split())
    given_tag_distribution = [topic for _, topic in given_tag_topics]
    tag_distribution = [topic for _, topic in tag_topics]
    cosine_sim = cosine_similarity([given_tag_distribution], [tag_distri
    similarity_scores.append((tag, cosine_sim))

similarity_scores.sort(key=lambda x: x[1], reverse=True)

# Measure the end time
end_time = time.time()

# Calculate the recommendation response time
response_time = end_time - start_time

#JUST comment these lines for overlap and Shannon’s entropy
# Display the results
print(f"Total Number of Recommendations: {num_recommended_tags}")
print(f"Recommendation Response Time: {response_time:.4f} seconds")
print("Top 5 Recommended Tags and Their Cosine Similarities:")
for tag, cosine_sim in similarity_scores[:5]:
    print(f"Tag: {tag}, Cosine Similarity: {cosine_sim:.4f}")
return total_recommended_tags  #JUST uncomment return statement for over
```

```
# User-defined given tag
given_tag = input("Enter your search variable: ")
total_recommendations_lda = lda_tag_recommendation(df, given_tag)  # JUST co
#JUST uncomment return statement for overlap and Shannon’s entropy
# recommended_tags_lda = lda_tag_recommendation(df, given_tag)
```

```
Total Number of Recommendations: 83
Recommendation Response Time: 0.0545 seconds
Top 5 Recommended Tags and Their Cosine Similarities:
Tag: bus, Cosine Similarity: 1.0000
Tag: build, Cosine Similarity: 1.0000
Tag: performing, Cosine Similarity: 1.0000
Tag: animal, Cosine Similarity: 1.0000
Tag: miscellaneous, Cosine Similarity: 1.0000
```

Overlap

In [ ]:

```
# Overlap
# Convert the lists to sets for efficient comparison
set_word2vec = set(total_recommendations_word2vec)
set_lda = set(total_recommendations_lda)

# Find the common tags by taking the intersection of the sets
common_tags = set_word2vec.intersection(set_lda)

# Count the number of common tags
num_common_tags = len(common_tags)

print(f"Number of Common Tags: {num_common_tags}")
```

```
Number of Common Tags: 75
```

Diversity

In [ ]:

```
# Shannon's entropy
import math

def calculate_entropy(recommendations):
    # Count the frequency of each recommendation
    freq = {}
    for rec in recommendations:
        if rec not in freq:
            freq[rec] = 1
        else:
            freq[rec] += 1

    # Calculate the total number of recommendations
    total = len(recommendations)

    # Calculate entropy
    entropy = 0.0
    for key in freq:
```

```
        prob = freq[key] / total
        entropy -= prob * math.log2(prob)

    return entropy
entropy_word2vec = calculate_entropy(total_recommendations_word2vec)
entropy_lda = calculate_entropy(total_recommendations_lda)

print(f"Entropy for Word2Vec Recommendations: {entropy_word2vec}")
print(f"Entropy for LDA Recommendations: {entropy_lda}")
```

```
Entropy for Word2Vec Recommendations: 11.66666784069043
Entropy for LDA Recommendations: 6.375039431346932
```